Prediction of drought-induced reduction of agricultural productivity in Chile from MODIS, rainfall estimates, and climate oscillation indices

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Abstract

Global food security is negatively affected by drought. Climate projections show that drought frequency and intensity may increase in different parts of the globe. These increases are particularly hazardous for developing countries. Early season forecasts on drought occurrence and severity could help to better mitigate the negative consequences of drought. The objective of this study was to assess if interannual variability in agricultural productivity in Chile can be accurately predicted from freely-available, near real-time data sources. As the response variable, we used the standard score of seasonal cumulative NDVI (zcNDVI), based on 2000–2017 data from Moderate Resolution Imaging Spectroradiometer (MODIS), as a proxy for anomalies of seasonal primary productivity. The predictions were performed with forecast lead times from one- to six-month before the end of the growing season, which varied between census units in Chile. Predictor variables included the zcNDVI obtained by cumulating NDVI from season start up to prediction time; standardised precipitation indices derived from satellite rainfall estimates, for time-scales of 1, 3, 6, 12 and 24 months; the Pacific Decadal Oscillation and the Multivariate ENSO oscillation indices; the length of the growing season, and latitude and longitude. For each of the 758 census units considered, the time series of the response and the predictor variables were averaged for agricultural areas resulting in a 17-season time series per unit for each variable. We used two prediction approaches: (i) optimal linear regression (OLR) whereby for each census unit the single predictor was selected that best explained the interannual zcNDVI variability, and (ii) a multi-layer feedforward neural network architecture, often called deep learning (DL), where all predictors for all units were combined in a single spatio-temporal model. Both approaches were evaluated with a leave-one-year-out cross-validation procedure. Both methods showed good prediction accuracies for small lead times and similar values for all lead times. The mean $R^2$ values for OLR were 0.95, 0.83, 0.68, 0.56, 0.46 and 0.37, against 0.96, 0.84, 0.65, 0.54, 0.46 and 0.38 for DL, for one, two, three, four, five, and six months lead time, respectively. Given the wide range of climates and vegetation types covered within the study area, we expect that the presented models can contribute to an improved early warning system for agricultural drought in different geographical settings around the globe.

1. Introduction

Droughts cause major agricultural production losses worldwide (Campbell et al., 2016). Although there is debate whether drought frequency has increased in recent years (Dai, 2012; Sheffield et al., 2012), climate change is expected to exacerbate the phenomenon and lead to more frequent and intense drought periods, which may even occur in regions where overall precipitation increases are expected (IPCC, 2013; McVicar et al., 2012; Trenberth et al., 2014; Wild, 2009). Although increased levels of carbon dioxide in the atmosphere may increase the water use efficiency of crops (Donohue et al., 2013; Lu et al., 2016; Zhu et al., 2016), the combined effects of global mean temperature (Zhao et al., 2017) and drought occurrence (Dai, 2012) are expected to cause an overall reduction of global crop yields (Ray et al., 2015; Zhao et al., 2017) and may have a negative impact on cropping frequency and sown area (Cohn et al., 2016). Planning for effective adaptation strategies is thus crucial to mitigate future impacts (Roco et al., 2014). In addition, the ability to anticipate the impact of drought early in the season and take in-season mitigation measures such as more targeted irrigation (e.g., by applying a regulated deficit irrigation), or
reducing stand density (Bodner et al., 2015) could help to reduce crop losses (Pulwarty and Sivakumar, 2014; Wilhite et al., 2000, 2014).

Satellite image time series have been widely used for monitoring agricultural drought (AghaKouchak et al., 2015). Commonly-derived variables from such time series include vegetation indices and rainfall estimates, which can be translated into anomalies by comparing the values in the current year against historic distributions (Ashouri et al., 2015; Funk et al., 2015; Huffman et al., 2007). The most commonly-used vegetation index for this purpose is the NDVI (Normalised Difference Vegetation Index; Rouse et al., 1974) from which multiple anomaly measures have been derived (Jiao et al., 2016; Kogan, 1990; Peters et al., 2002; Sandholt et al., 2002) and applied for monitoring agricultural drought (Cunha et al., 2015; McVicar and Jupp, 1998; Rojas et al., 2011; Zambrano et al., 2016; Zhang and Jia, 2013). Besides NDVI, other vegetation indices have been developed with the aim to further increase the sensitivity to vegetation activity, including the enhanced vegetation index (EVI; Huete et al., 2002) and the Vegetation Index based on the Universal Pattern Decomposition (VIUPD; Zhang et al., 2007). An often-used approach to translate rainfall information into a meteorological drought measure is through the calculation of the Standardised Precipitation Index (SPI; McKee et al., 1993), an anomaly measure that is closely related to soil moisture availability when computed for short time scales (i.e. < 9 months) (Quiring and Ganesh, 2010). While the SPI can be calculated from weather station data, in countries with a low station density and short historical records, satellite-derived rainfall estimates (RFE) can be a good alternative source for SPI calculation (Tapiador et al., 2012; Zambrano et al., 2017). Other satellite-derived products that have relevance for drought monitoring include estimates of soil moisture and evapotranspiration (Hao and AghaKouchak, 2013; Mu et al., 2013; Sheffield et al., 2004; Tsakiris et al., 2007). Drought indices are also constructed by combining multiple parameters. For example, the SPEI (Standardised Precipitation Evapotranspiration Index) considers both precipitation and evapotranspiration to account for the effects of temperature variability on drought assessment (Vicente-Serrano et al., 2010) and has been used in various studies for monitoring agricultural drought (Moorhead et al., 2015; Potopová et al., 2015; Vicente-Serrano et al., 2012). Climate-based drought indicators and satellite-derived vegetation metrics with other biophysical information are used by the United States National Drought Mitigation Center to calculate the Vegetation Drought Response Index (VegDRI, J.F. Brown et al., 2008; Brown et al., 2008) by analysing historical input data with a regression tree approach that produces a map of drought conditions. While we can accurately assess and monitor agricultural drought as it occurs with a variety of indices, early prediction is more complex.

The prediction of vegetation conditions is challenging for three reasons: 1) the underlying uncertainties in weather and climate prediction (Morsø et al., 2008); 2) changes in precipitation patterns (Dore, 2005), such that precipitation amount and distribution may substantially deviate from normal regional patterns; and 3) the effect of both of these on crop production which in turn depends on land management decisions and the sensitivity of different crop stages to the intensity and duration of water shortage or excess (Knapp et al., 2008; Sykes, 2001), amongst other factors. Despite this challenge, various efforts have been made to predict vegetation conditions. Table 1 provides a non-exhaustive overview of relevant studies that aim to predict agricultural productivity, or a related proxy, from remote sensing-derived predictors.

Several studies have used a single predictor to explain the inter-annual variability in seasonal vegetation productivity. In those cases, early prediction was achieved by using lagged relationships whereby the predictor was available before the end of the season (Meroni et al., 2014; Vrieling et al., 2016). Alternatively, rainfall has been used as a predictor of seasonal vegetation productivity. For example, Meroni et al. (2017) found for the Sahel that on average about 40% of the variability in seasonal vegetation productivity could be explained by selecting the optimal time-scale and timing of SPI per grid cell. In addition, climatic oscillation indices, such as the Pacific Decadal Oscillation (PDO) and the Multivariate ENSO Index (MEI), have been shown to affect weather across the globe and can explain variability in agricultural productivity (Boisier et al., 2016; Garraud and Battisti, 1999; Hansen et al., 1998; Marj and Meijerink, 2011; Montecinos and Aceituno, 2003; Reilly et al., 2003).

Brown et al. (2010) demonstrated that the timing of the growing season cumulative NDVI depends significantly on the PDO and the MEI across multiple locations in Africa. Van Leeuwen et al. (2013) showed that the MEI and Antarctic Oscillation (AAO) index could explain part of the interannual variability in annual NDVI-based productivity and phenology for South America. While these studies assessed the explanatory power of climatic oscillation indices on vegetation variability, they did not specifically address the prediction of vegetation productivity shortfalls before they occur. Although studies focusing on single parameters offer interesting directions for the prediction of vegetation productivity, combining multiple predictors could increase the prediction skills.

The use of multiple predictors to estimate vegetation response has been evaluated by applying different techniques such as multiple linear regression models and regression trees. Commonly-used predictors include lagged NDVI, precipitation-derived indices such as SPI, soil moisture, and oscillation indices (Table 1). Optimal prediction skills of NDVI variability range approximately between 90% (one month before) and 50% (three months before), as achieved for example by Tadesse et al. (2014). More recently, machine learning methods have been used for predicting daily and monthly rainfall (Abbot and Marohasy, 2012, 2014; Deo and Şahan, 2015; Nastos et al., 2014), mostly because they can accommodate a large number of input variables and can automatically combine these into complex functions that describe multiple, non-linear relationships between the independent and explanatory variables (LeCun et al., 2015). Given the mentioned advantages of machine-learning methods and the lack of current drought prediction tools, there is scope to evaluate if machine learning methods could provide more accurate early prediction of drought than linear regression models.

The main goal of this study is to assess if interannual variability in crop biomass productivity can be accurately predicted using freely-available, near real-time data sources. The sources included NDVI time series, anomalies of cumulative rainfall at different monthly time-steps obtained from satellite-derived RFEs, and climatic oscillation indices. To achieve our goal we tackle the following objectives: (i) derivation of a proxy for seasonal crop biomass productivity for the growing season; (ii) development of two prediction models for that proxy, one based on optimal linear regression model (OLR) per spatial unit, and the other combining information from all units in a feed-forward multi-layer neural network, known as deep learning (DL); and (iii) evaluation of the OLR and DL model predictions for the period 2000–2017. The Methods, Results and Discussion sections are structured according to these three objectives.

2. Study area

We selected Chile as a case study area for this analysis, because it contains a large diversity in climate and crops, and frequently suffers from drought-induced crop losses (Zambrano et al., 2016). Future crop losses can be expected because a decrease in precipitation is predicted for the Central and South part by the global climate models (IPCC, 2013) where about 84% of the agricultural activities are concentrated (INE, 2007). As a result, wheat and maize yields for Chile are expected to decrease by about 15% to 20% by 2050 (IPCC, 2014; Meza and Silva, 2009) based on crop growth simulation models with future climate scenario data. During the past decade, an unusual long period of dry conditions persisted over Central Chile and has been termed a mega drought (Garraud et al., 2017). The focus of this study is the main...
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<sup>a</sup> SST: Sea Surface Temperature.  
<sup>b</sup> LST: Land Surface Temperature.  
<sup>c</sup> SOI: Southern Oscillation Index (SOI).  
<sup>d</sup> NAO: North Atlantic Oscillation (NAO).
agricultural area of Chile, which is located between 29° and 41°S and comprises about 95% of the cultivated land in the country (INE, 2007) corresponding to 19,407 km². Although semi-arid (Bwk = 5.5%; Bsk = 5.6%) and humid climates (Csc = 0.2%, Cfb = 15%) are found in the study area, the dominant climate is temperate Mediterranean (Csb = 64%) according to the Köppen climate classification system (Kottek et al., 2006; Peel et al., 2007). The main proportion of agriculture in Chile is located in the Central Valley (Fig. 1a), which corresponds to the depression between the Chilean Coastal Range and the Andes Mountains, with elevation ranging from 200 m to 400 m (Fig. 1b). Mean annual precipitation varies from < 300 mm in the north to 1800 mm in the south (Fig. 1c). Cultivated land north of 32°40′S is used for fruit production, vineyards, and horticulture in the transversal valleys that run east-west from the Andes to the Pacific. Fruits, vineyards, industrial crops, and horticulture dominate between 32°40′ and 37°42′S. Further south, the land is mainly used for raising cattle for beef and dairy production, and includes croplands with cereals, and to a lesser extent fruits (ODEPA, 2015).

The current census units were selected as the spatial analysis unit in this study since they are used for the agricultural survey performed every decade by the Chilean government (INE, 2007). The mean area for the 758 units is 80.4 km², ranging from 9.6 km² to 360 km² with a standard deviation of 51.9 km². These units are large enough to not be affected by crop rotation patterns due to satellite-derived greenness measures used in this study. At the same time, the units are small enough to capture spatial variability in the main cropping systems in the study area. By adopting this segmentation we improve the spatial detail of agricultural productivity monitoring compared to the current drought declaration scheme applied by the government, which uses larger administrative units (264 in the study area) that may have a strong internal heterogeneity in terms of cropping systems. The study area contains a total of 2212 census units. The cropland spatial distribution is shown in Fig. 1a, which indicates that the most intensively cultivated area is located between 34° and 37°S.

3. Data

3.1. Vegetation

Data from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor were used to delimit the spatial extent of the main agricultural area of Chile, to define the growing season, and to derive a proxy-measure of seasonal vegetation productivity anomalies. To derive a cropland mask over the study area the IGBP Land Cover Type layer from the latest available MCD12Q1 product (Collection 5.1) (Friedl et al., 2010) was selected that contains annual maps for 2001 to 2013 at 500 m spatial resolution. From the MCD12Q2 Collection 5 product (Ganguly et al., 2010) we extracted start-, end-, and length-of-season (SOS, EOS, LOS, respectively), which is provided at annual intervals for 2001 to 2014 at 500 m spatial resolution. To assess productivity anomalies, we used 500 m resolution 16-day NDVI composites (product MOD13A1, Collection 6) for the period 2000 to 2017. NDVI was chosen rather than other vegetation indices (Huete et al., 2002; Jiao et al., 2016), because i) NDVI is a commonly-used indicator in drought monitoring efforts; ii) it can be derived from many data series including those lacking a blue band (e.g. the Advanced Very High Resolution Radiometer); iii) for the selected study area the Chilean government is already using NDVI as an indicator for drought monitoring. To reduce remaining atmospheric noise, we smoothed the NDVI time series using a locally-weighted polynomial regression (LOWESS) as described by Zambrano et al. (2016). All MODIS data were obtained through the online Data Pool at the NASA Land Processes Distributed Active Archive Center (LP DAAC) and USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota (https://lpdaac.usgs.gov/).

3.2. Precipitation

We used a satellite-derived RFE product for precipitation instead of rain gauge information due to gaps in the historical station data and the...
low density of rain gauges in the study area. We selected the 0.05′ spatial resolution, dekadal (10-day period) RFE dataset of CHIRPS (Climate Hazards Group InfraRed Precipitation with Station) (Funk et al., 2015) version 2.0 for 1981 to 2017, which has recently been evaluated over Chile and shown to be a good alternative for rain gauge measurements (Zambrano et al., 2017; Zambrano-Bigiarini et al., 2017). Zambrano et al. (2017) showed that the $R^2$ between in-situ and CHIRPS v2 monthly rainfall was above 0.77 between latitudes 33° and 40°S. They found that CHIRPS-derived SPIs at one, three, and six months showed fair accuracies with root mean square errors (RMSE) ranging from 0.6 for Central (32°–36°S) to 0.79 for South-Central (36°–40°S) Chile when compared against SPIs derived from in-situ rainfall data. In the Center, the $R^2$ was consistently about 0.64 throughout the year, except for the normally dry summer months (January to March) for which $R^2$ was below 0.36. For the South, the $R^2$ ranged from 0.49 in February to 0.64 in December (Zambrano et al., 2017).

3.3. Climatic oscillation indices

Because of their demonstrated effect on vegetation productivity and phenology in South America (Van Leeuwen et al., 2013), we used two climate oscillation indices: 1) the PDO that is often described as a long-lived El Niño-like pattern of Pacific climate variability (Zhang et al., 1997); and 2) the MEI, which corresponds to the first component of a principal component analysis (PCA) based on six observed variables over the tropical Pacific (30°–30°S, and 100°E–70°W), including sea-level pressure, zonal and meridional components of the surface wind, sea surface temperature, surface air temperature, and total cloud fraction (Wolter and Timlin, 2011). Both indices were provided by the National and Oceanic Atmospheric Administration (NOAA) at a monthly time step. (PDO and MEI datasets were obtained from https://www.ncdc.noaa.gov/teleconnections/pdo/ and https://www.esrl.noaa.gov/psd/enso/mei/table.html).

4. Methods

4.1. Deriving a proxy for seasonal crop biomass productivity

4.1.1. Selection of census units

Because our study focuses on agricultural productivity, only census units were selected that had a predominance of croplands. We selected the class croplands (class 12) from the IGBP (International Geosphere-Biosphere Programme) classification scheme contained in the MCD12Q1 data. A cropland mask was created from 13 years (2001–2013) of MCD12Q1 (see Fig. 2). Per grid cell, the percentage of years for which the IGBP classification scheme of MCD12Q1 indicated cropland was calculated as a measure of cropland persistency. Then we applied a threshold to this percentage to create a single cropland map in order to consistently monitor the same areas. To choose the most appropriate threshold level that best describes actual cropland distribution, 585 grid cells of 500 × 500 m² resolution were selected following a regular-random combined sampling. Out of these 585, 485 grid cells were obtained by placing a regular grid of 18 × 18 km² over the study area. Another 100 grid cells were added through random sampling within the most intensively cultivated area. This was done with the aim of having a balanced number of samples of cropland and no cropland. To assess which crop persistency provides a reasonable description of the crop distribution, we visually interpreted high-resolution (< 5 m) imagery from Google Earth to identify agricultural fields and estimated the areal fraction of cropland (between 0% and 100%) within each sample grid cell. For this purpose, only Google Earth imagery that was acquired within the same time frame of the MCD12Q1 product (2001–2013) was used. Grid cells with > 50% cropland cover were labelled as cropland. The 585 samples were subsequently compared with the masks obtained using different threshold levels of MCD12Q1-derived cropland persistency. A threshold of 30% resulted in the highest global accuracy with the photo-interpreted set (i.e., 78%), as well as when compared against a mask derived from data provided by the Ministry of Agriculture of Chile (INE, 2007) (i.e., 80%). Given the high accuracy and the compatibility of its spatial resolution with our other input data, the 30% persistency threshold was selected for making the cropland mask for this study.

We then used the cropland mask to calculate the percentage of cropland area within each census unit (Fig. 1c). Census units for which the cropland area did not reach 10% of its total area and/or was smaller than 750 ha (30 grid cells) were excluded from the analysis in order to keep only those units where agriculture is an important activity based on its spatial extent. This resulted in 758 census units.

4.1.2. Defining the growing season per census unit

The unit-level average growing season period was defined using the MCD12Q2 land surface phenology product over the period 2001 to 2014. For the start and end of season (SOS and EOS) we used the layers Onset Greenness Increase and Onset Greenness Minimum, respectively. Although bi-modality was present in the MODIS product, we retained the only agronomic season occurring in Chile, roughly between September and April. The multi-annual average of SOS and EOS was calculated for each cropland grid cell that had at least 50% of valid phenology retrievals for the period 2001–2014. Across Chile, about 5% of the identified cropland grid cells did not meet this requirement, because of persistent clouds and limited variability of the enhanced vegetation index (EVI, used as input for MCD12Q2) in years of drought (Zhang et al., 2009). Finally, we calculated a unit-level SOS and EOS as the median value for all crop grid cells within each unit, and LOS as the difference between the two. As the median phenological events are expressed as day of year, we linked them to the 16-day time step of the MOD13A1 composites by rounding off SOS and EOS to the nearest start and end date of the compositing periods, respectively.

4.1.3. Deriving a proxy for seasonal crop biomass production

Accurate spatio-temporal data on crop production in Chile were not available and as a consequence we used NDVI to construct a proxy variable for seasonal crop biomass productivity. In various studies, the cumulative value of NDVI over the growing season has been used as a proxy of biomass production (Prince, 1991; Tucker et al., 1985; Schucknecht et al., 2017; Wang et al., 2005; Paruelo et al., 2016; Jobbagy et al., 2002; Helman et al., 2014) and crop yield (e.g. Funk and Budde, 2009; Meroni et al., 2013). The cumulative NDVI ($c$NDVI) over the growing season (S) was thus derived per unit and per season as:

$$c$NDVI$^S = \sum_{t=SOS}^{EOS} NDVI^t$$

where the SOS and EOS vary per unit and $t$ refers to each 16-day NDVI composite.

We transformed the $c$NDVI into a standardised anomaly to reflect how much the primary productivity of the cropland is above or below normal. This can be written as:

$$\frac{c$NDVI$^S - \bar{c$NDVI$^S}}{\sigma(c$NDVI$^S)}$$

where $c$NDVI corresponds to the unit-level multi-annual average and $\sigma(c$NDVI) to the standard deviation of cNDVI between the 2000–2001 and 2016–2017 seasons.

4.2. Developing OLR and DL prediction models

4.2.1. Predictor variables

A number of predictor variables were selected based on previous studies that evaluated the predictability of drought. We incorporated variables that could be derived from data sources that span the entire
time frame of analysis (2000–2017), that are available in near real-time, and (for spatially varying variables only) have a grid size for which each census unit is contained by multiple grid cells. These include:

1. Z-scored cumulative NDVI ($zc_{NDVI}$), taking as the temporal integration period the interval between SOS and the time of prediction, i.e. $\tau$ equal to one, two, three, four, five, and six months lead time (time before EOS). Because the NDVI data are 16-day composites, effectively we analysed the integration time periods from SOS to 32, 64, 96, 128, 160, and 192 days before EOS, but still refer to these as one to six months lead time in this paper. We note that for some units the LOS is not long enough to accommodate all lead times. In Sections 4.2.2 and 4.2.3 we specify how we dealt with that.

2. SPI at time-scales of 1, 3, 6, 12, and 24 months, each of which is calculated one to six months before EOS. We used the SPI to describe precipitation deficit because it is the most important driver of agricultural drought. We can expect a high correlation between SPI and soil moisture (Xu et al., 2013) particularly for the temperate Mediterranean climate of the study area (Yang et al., 2018). We refer to these as $SPIT_{\tau}$, with $T$ being the time-scale and $\tau$ the lead time in months. Previous studies have shown that SPI can explain part of the variability in vegetation productivity, for example in the Sahel (Meroni et al., 2017) and in South-Central Chile (Zambrano et al., 2016). For this study we calculated SPI from dekadal CHIRPS data. For each dekad (10-day period), we first calculated the cumulative rainfall over a one, three, six, 12 and 24 month period before the end date of the dekad and subsequently transformed this into a corresponding SPI. For SPI calculation, a Gamma distribution was adjusted using a method for parameter fitting based on unbiased Probability Weighted Moments (Vicente-Serrano et al., 2010). To compute the SPI the ‘SPEI’ package (Beguería and Vicente-Serrano, 2013) within the R environment (R Core Team, 2018) was used. While short time scale SPIs (less than nine months) are reported to relate most strongly to agricultural drought (Quiring and Ganesh, 2010; Rhee et al., 2010), we included the 12- and 24-month time scales to account for a possible memory effect on vegetation response (Richard et al., 2008).

3. Climate oscillation indices. Following previous studies linking variability of precipitation and vegetation productivity to climate oscillations indices (see Section 1), we considered the monthly MEI and the PDO oscillation indices. We temporally averaged each of these two indices for three non-overlapping time windows of three months preceding the time of prediction. The first temporal window ranges from the time of prediction to three months before the time of prediction, the second from six months before to three months before and the third from nine months before to six months before. Considering that predictions are made for six lead times during the growing seasons, this results in 18 variables per climatic index. We denote this as $MEI_{3l\tau}$ and $PDO_{3l\tau}$, whereby $3$ refers to the three month window used for averaging, $l$ is the lag time (in months) preceding the time of prediction, and $\tau$ still refers to the forecasting lead times (also in months).

4. Length of season (LOS). The magnitude of unit-level cNDVI depends on the average NDVI magnitude during the season, as well as on the LOS. Because the LOS used here has a fixed value through the seasons reason for which is useless as predictor for OLR per unit, here just for the DL approach we added LOS to characterise and possibly group units (in addition to point 5 and 6 hereafter).

5. Latitude and longitude. To account for location-dependent relationships between $zc_{NDVI}$ and the predictors that would otherwise be missed in the DL model (which considers all units), we incorporated the latitude and longitude of the centroid for each unit as additional predictors. Latitude has a strong relation with the north-south climate pattern (see Fig. 1b), whereas longitude links to an east-west elevation pattern (see Fig. 3a). Also, rainfed crops are mainly located to the west, near the coast.

6. Clusters for vegetation-precipitation. We made four clusters for the DL model with the aim of providing a coarse zonation according to climate and vegetation characteristics. These categorical clusters

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**Fig. 2.** Schematic diagram of the processing steps for generating input data for the prediction models. One to six months lead time was considered from the end of growing season (EOS).
were derived from a k-means classification over the 758 units based on the multi-annual (2000–2017) average and standard deviation of cNDVI, the per-unit annual average precipitation, and LOS.

4.2.2. Prediction by OLR

Linear regression relationships were derived for each unit with the purpose of finding a single predictor variable that best explains the 17-season temporal variability of zcNDVI per unit before the end of season (i.e. one to six months in advance). Optimal in OLR refers to the model with the smallest cross-validated root mean square error (RMSE; see Section 4.3) for the evaluated prediction lead time. The 12 independent variables included for each lead time were described in Section 4.2.1: SPI1, SPI3, SPI6, SPI12, SPI24, PDO30, PDO33, MEI0, MEI6, MEI6, MEI6, MEI6, zcNDVI. If the lead time exceeded the LOS for a specific unit, zcNDVI could not be calculated because the growing season had not yet started. In those cases we used the remaining eleven predictors. Generalising the notation of each predictor (P) per unit and forecasting lead time to \( P^* \), we can express the general linear equation as:

\[
zcNDVI^* = a \cdot P^* + b
\]

4.2.3. Prediction by DL

For each prediction lead time \( r \), a single DL model comprising the same predictors and dependent variables for all units was trained and evaluated (LeCun et al., 2015). The DL model was implemented using the H2O Java platform, a scalable and open source machine learning and deep learning package that uses multi-layer feed-forward (MLF) neural networks (Candel et al., 2016). We used the interface adapted for the programming language R (Aiello et al., 2016). MLF neural networks consist of neurons that are ordered into layers. Hidden layers connect input layers with an output layer, allowing for multiple connections with varying strength (Svozil et al., 1997). The connections are formed during the training of the network whereby the ultimate aim is to accurately predict the output layer. Having multiple levels of hidden layers and connections between them permits the formation of complex relationships between inputs and outputs (LeCun et al., 2015). Due to the complexity of the layer levels and their possible connections, the term deep learning is often used to describe such networks. We limit ourselves here to describing how we trained the model, set its parameters, and how the importance of the predictors was evaluated. The reader is referred to Candel et al. (2016) and LeCun et al. (2015) for a more complete description of the MLF neural network architecture.

DL models for each prediction lead time were created for the entire study area by considering all units simultaneously. For each lead time \( r \) and validation year, the parameter values for the DL model were adjusted by the random grid search procedure (Bergstra and Bengio, 2012; Candel et al., 2016) to find the optimal DL model that produces the smallest mean absolute error (MAE). Thus, for each parameter a defined list of optional values is provided to the model framework from which the random grid search selects the optimal parameter value combination. Table 2 lists those parameters and the possible values fed to the random grid search. For search iteration the parameter epochs was set to 1000. For additional parameters, we used the default values for function h2o.deeplearning in R (see Aiello et al., 2016). For each prediction lead time 17 models were trained, each one obtained using a different set of 16 seasons of data out of the 17 available. That is, we trained the DL models leaving one season out for validation (see Section 4.3). Then, in each run of the leave-one-out process, we used 70% of the 16 years data for training allowing the DL to find the optimal parameter values to fit the data. Per model run, the remaining 30% was used for re-adjusting the DL parameters by following the approach known as the holdout method. For units with a shorter LOS than the analysed lead time the zcNDVI could not be calculated, and was replaced with the average zcNDVI value of all the remaining units.

The Gedeon method (Gedeon, 1997) was used in H2O to assess the relative importance of each variable per DL model. This method uses the matrix of connection weights between the layers of the trained neural network to determine which inputs most significantly influence the model results. The connection weights between neurons are tallied for each input node and scaled, relative to all other inputs, between zero and one. Thus, the relative importance corresponds to the degree

![Image](70x523 to 525x737)

*Fig. 3.* Growing season (a) start date (SOS) and (b) end date (EOS) per census unit; (c) legend used for panels (a) and (b) following Vrieling et al. (2016); the outer circle represents the first 10-day period of each month; (d) growing season length per census unit. All were derived from the MCD12Q2 Collection 5 product.
of association between each predictor and the proxy response relative to all other predictors. We applied the Gedeon method to identify which variables had more significance in the final model for each prediction lead time, thus allowing for comparison with the variables selected by the OLR method.

4.3. Evaluating the prediction models

To evaluate the accuracy of the predictions and to compare between the OLR and the DL models, we used the coefficient of determination ($R^2$), RMSE and the MAE between modelled and observed data. We calculated these statistics using a leave-one-year-out cross-validation, which leaves out one season at a time, permitting a comparison between the observed $z c N D V I^S$ and the corresponding value predicted independently from the remaining observations ($z c N D V I^F$). For example, for each census unit the RMSE$_{cv}$ is calculated as:

$$RMSE_{cv} = \sqrt{\frac{\sum ((z c N D V I^S - z c N D V I^F)^2)}{n}}$$

where $n$ is the number of seasons.

The statistics were computed for the prediction obtained by both methods (OLR and DL) and each lead time. We then summarised the distribution of $R^2_{cv}$ and RMSE$_{cv}$ in boxplots.

To further analyse the spatial variability of the predictive power, we evaluated if the explained variability ($R^2_{cv}$) was significantly different for units located in three zones with contrasting agro-climatic conditions (see Section 2): 1) North, census units north of 32.4°S, 2) Centre, for units between 32.4°S and 37.42°S, and 3) South, for those south of 37.42°S. In addition, we evaluated if season length affected the prediction accuracy by plotting $R^2_{cv}$ against LOS. Furthermore, we graphically compared the time-series from 2000 to 2016 of $z c N D V I^S$ against the prediction ($z c N D V I^F$) made by OLR and DL in four census units spanning the range of variation of vegetation productivity and season length. From each cluster defined in Section 4.2.1 (item 6) we randomly selected one census unit and plotted the observed $z c N D V I$ time series for the 2000–2016 seasons together with their predictions at one to six months lead time for both prediction methods (OLR and DL). Finally, to evaluate the prediction quality particularly for drought or wet conditions, we pooled the $z c N D V I^F$ observations for all the units and classified them into 10 classes. For each class and prediction lead time we calculated the RMSE$_{cv}$ to compare the ability of both prediction models to predict drought.

5. Results

5.1. Deriving a proxy for seasonal crop biomass productivity

The analysis of phenology revealed an east-west pattern for SOS (Fig. 3a), with the SOS in May and June for units in the west, and predominantly in July and August in the east. While the EOS pattern is somewhat similar, Fig. 3b also shows that in the south EOS is generally earlier (February/March) as compared to the north (April/May). As a result, shorter LOS values (< 250 days) are found south of 38°S whereas longer seasons are found in the north (Fig. 3c). The isolated units in the far north part of the study area have an SOS of around August–September, an EOS between April and June, and a LOS of 250–300 days.

Fig. 4 shows the distributions for $z c N D V I$ over the 758 units for season 2000–2001 to 2016–2017, indicating that most units had values below zero for the seasons 2007–2008 and 2008–2009, corresponding to the most severe agricultural drought since the year 2000. This is supported by Zambrano et al. (2016, 2017) and by the declaration of drought emergency made by the Ministry of Agriculture of Chile.

To assess if the seasonal crop biomass productivity proxy used in this study is accurate, comparison against actual crop production data would be required.
Although zcNDVI was the most frequently selected predictor for all prediction lead times, for the South region the SPI1 was selected for 51 units (out of 758) for predictions with four months lead time; for five months the best predictors after zcNDVI were MEI3 (65 units) and MEI30 (39 units); for six months MEI3 was selected for 115 units, SPI24 for 24 units and SPI6 for 23 units. However, for units where other predictors than zcNDVI were selected, the $R^2$ was generally small and $\text{RMSE}_{cv}$ and $\text{MAE}_{cv}$ were large compared to those where zcNDVI was selected.

### 5.3. Evaluating the prediction models

On average the DL and OLR models had similar accuracies across the 758 census units, as evidenced in mean $R^2$, $\text{RMSE}_{cv}$ and $\text{MAE}_{cv}$ values for all prediction lead times (Fig. 5a). Also, the dispersion of $R^2$ and $\text{RMSE}_{cv}$ values were similar for both models (Fig. 5a and b). Although for OLR the zcNDVI was the most selected predictor for the six lead times, as we move to the longer lead times we observe that the climatic indicators become more relevant and there is a spatial north-south pattern. However, OLR results in location-independent models. In DL, location is specifically incorporated by means of the predictors’ latitude and longitude, as well as the four clusters. While for short lead times, zcNDVI is indeed by far the most important variable in the DL model (Fig. 10), both location and climatic variables have an increased importance when moving to longer lead times. For the North, OLR predictions were more accurate than DL predictions for all lead times (Fig. 6c). The better performance of OLR in the North could be attributed to two reasons: 1) given the long season length (> 250 days, Fig. 3d), the partial zcNDVI is calculated when a large part of the season has elapsed already, and can consequently explain much of the zcNDVI\textsuperscript{2} variability (Fig. 8), even for longer lead times; and 2) the SPI and climatic indices may not have a large impact on crop water availability in this semi-arid climate in which crop production depends highly on irrigation. For the Centre, the values for both $\text{RMSE}_{cv}$ and $R^2$ did not show differences between OLR and DL. For the South, DL predictions were slightly more accurate than those from OLR for lead times between 2 and 5 months (Fig. 6c).

Fig. 11 shows the time series of observed and predicted zcNDVI\textsuperscript{2} for each growing season from 2000 to 2001 to 2016–2017, for the four units selected by the cluster analysis. The census unit Pan de Azucar is located in the most arid part of the study area and has a long season of 284 days; only irrigated crops are grown here. The Santa Cruz unit represents units with intermediate levels of annual rainfall of 720 mm and zcNDVI of 9, combined with a fairly long season of 244 days. The Quintrilpe unit has the largest amount of average annual rainfall (1585 mm), but a lower zcNDVI (8) due to a shorter LOS of 179 days.

### Table 3

Prediction accuracies measures $R^2_{cv}$ and $\text{RMSE}_{cv}$ calculated in a one-leave-out cross validated approach for one to six month lead forecasting time with OLR and DL models over the 758 units and 17 growing seasons. No significant differences with paired $t$-test, $p < 0.01$ for $R^2_{cv}$ and $\text{RMSE}_{cv}$.

<table>
<thead>
<tr>
<th>Lead time (months)</th>
<th>OLR</th>
<th>DL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$R^2_{cv}$</td>
<td>$\text{RMSE}_{cv}$</td>
</tr>
<tr>
<td>1</td>
<td>0.95</td>
<td>0.21</td>
</tr>
<tr>
<td>2</td>
<td>0.83</td>
<td>0.38</td>
</tr>
<tr>
<td>3</td>
<td>0.68</td>
<td>0.52</td>
</tr>
<tr>
<td>4</td>
<td>0.56</td>
<td>0.62</td>
</tr>
<tr>
<td>5</td>
<td>0.46</td>
<td>0.70</td>
</tr>
<tr>
<td>6</td>
<td>0.37</td>
<td>0.77</td>
</tr>
</tbody>
</table>
The last unit analysed was Cocule, with large annual rainfall (1242 mm) and an average cNDVI of 10 with a shorter season length of 213 days. Overall, both models represent the temporal pattern of zcNDVI reasonably well and show decreasing accuracy with increasing prediction lead time. The predictions were most accurate for Pan de Azucar. The accuracy decreased going southwards via Santa Cruz and Quintrilpe to Cocule. This latitude dependency corresponds with the Rcv^2 pattern showed in Figs. 7 and 9. Predictions made shortly before EOS (lead time = 1) are in all cases more accurate than those made with longer lead times. Out of these four units, OLR outperformed DL for Pan de Azucar and Santa Cruz for all prediction lead times. Nonetheless DL outperformed OLR predictions for most of the other lead times in Quintrilpe, and Cocule.

Fig. 12 plots unit-level Rcv^2 as a function of LOS for OLR and DL. It shows that the accuracy of the predictions decreases for shorter LOS and this effect becomes stronger as we increase the lead time used for the prediction.

Fig. 13 shows that deviations between predicted and observed zcNDVI increase towards the more extreme z-score classes. Extreme droughts (zcNDVI < −2) were identified during the period

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**Fig. 6.** Comparison of accuracy measures between DL and OLR for the 758 census units by boxplots of: a) Rcv^2, b) RMSEcv, and c) spatial aggregation into North (29.0°–32.4°S), Centre (32.4°–37.4°S) and South (37.4°–40.7°S) zones; for one, two, three, four, five and six months lead time.

**Fig. 7.** Interannual variance of season zcNDVI explained (Rcv^2) when predicting by OLR considering per unit and time lag a single optimal predictor variable for: a) one, b) two, c) three, d) four, d) five, and e) six months lead time.

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2000–2017, for 243 unit-season combinations with prediction errors between 0.2 (lead time = one month) and 1.5 (lead time = six months). For the more extreme z-score values (−2 to −3), OLR outperformed DL for four to six month lead times.

6. Discussion

6.1. Deriving a proxy for seasonal crop biomass productivity

Although the MCD12Q2 provided a spatially-explicit overview of growing season definitions, its season definitions may not be tailored to the precise period of crop growth. Because MODIS grid cells may be partially covered by natural vegetation, the resulting phenology is a mixture of the crop and the natural vegetation. It is likely that natural vegetation has an earlier SOS and a later EOS compared to crops, which are normally harvested before natural vegetation has come to complete senescence. The MCD12Q2 product determines SOS/EOS through curvature change in a logistic model representation of the EVI time-series within the mixed pixel, resulting in a relatively early SOS and late EOS, compared to the crop SOS and EOS (Zhang et al., 2006). Other agricultural drought studies have brought the EOS forward to better reflect the end of grain filling (Rojas et al., 2011). In this regard, spatially explicit crop calendar information for Chile would better define this seasonality, allowing for better proxies of agricultural productivity, and more relevant timing of drought prediction.
Fig. 10. Mean variable relative importance derived from deep learning models for 17 models (2000–2001 and 2016–2017 growing seasons) for one to six months lead time. Per column, values are colour-coded from light (small) to dark (large).

Fig. 11. Comparison of the prediction of zcNDVI for four census units and for one to six months lead time obtained by a) OLR, and b) DL models; against the observed zcNDVI. For each census unit the centre location is provided, together with the unit’s average annual rainfall ($R$), average cumulative (cNDVI), and the length of seasons (LOS). The location of these units in Chile is shown in Fig. 1c.
6.2. Performance comparison of OLR versus DL models

We analysed the drought prediction skill for one to six months lead time at census unit level. However, since LOS varies between the units, the prediction timing could represent a different progress of the season. For example, for an LOS of eight months, already half of the season has passed at a lead time of four months, so more information on that season performance is available as compared to a LOS of five months. For operational applications, a question is whether it is more useful to have a prediction at a fixed number of months before EOS, or alternatively if the prediction should relate to a relative measure of season progress. For example, Meroni et al. (2017) predicted $z_cNDVI$ from SPI for 0, 25, 50, and 75% of season progress. We note that in our current set-up, the DL model could have suffered from the mixing of areas with different completeness of information on seasonal performance (due to varying LOS). LOS decreases from north to south (Fig. 3c), following a similar pattern to the variability explained ($R^2_{cv}$) by both modelling approaches (Figs. 6 and 8), resulting in a relationship between LOS and $R^2_{cv}$ (Fig. 11) becoming stronger with longer prediction lead times. Although $z_cNDVI^i$ was in general the best predictor of $z_cNDVI^p$, the prediction accuracy strongly depended on the prediction lead time for both OLR and DL with poor predictive power early during the season.

Further, we also tested a multiple linear regression (MLR) model considering all the predictors per unit, but this resulted in very poor cross-validation statistics due to the strong overfitting that occurred in the presence of 12 predictors and only 17 seasonal observations per unit (Harrell, 2006). Thus, a simple regression method (OLR) that selects just one predictor per unit yielded only a slightly smaller accuracy as compared to a more complex method (DL) which uses several predictors for all units. Similar results were obtained in other studies that compared neural networks with regression and found no, slightly, or even significantly better performance of regression over neural networks in some cases (Shaker et al., 2014; Kumar, 2005). Our study therefore shows that complex global models do not always yield better results than simple models that carefully select the best predictors on a case-by-case basis.

In addition, OLR has some advantages compared to DL. For example, OLR allows for a unit-specific identification of which predictor is the most efficient in estimating $z_cNDVI$ (i.e. explaining the highest fraction of its variance). This allows mapping the selected predictors

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Fig. 12. Scatterplots between LOS (x-axis) and the amount of $z_cNDVI$ variance explained (y-axis) for the OLR and DL prediction models, including the trend line, for a) one, b) two, c) three, d) four, e) five, and f) six months lead time.

Fig. 13. RMSE$_{cv}$ variation for OLR and DL prediction models as a function of lead time (in months on x-axes) or different levels of $z_cNDVI$. The grouping in ten classes was done following a combination of all $z_cNDVI/z_cNDVI^p$ values for all units.
and getting insights on the impact of weather variables in vegetation development.

Despite the potential for further improving our models, in this study we reached an average prediction accuracy ($R^2$) between 0.37 and 0.96 depending on the prediction lead time. Several other studies predicted seasonal cumulative vegetation indices within season (see also Table 1). For example, Meroni et al. (2017) showed that SPI could explain about 40% of the zcNDVI variability. Asoka and Mishra (2015) obtained $R^2$ values between 0.14 for three months, and 0.89 for one month lead time. Tadesse et al. (2014) predicted monthly NDVI with three and one month lead time reaching a maximum $R^2$ of 0.50 and 0.90, respectively. As such, our current results are encouraging given that they reach similar or better accuracy compared to existing studies.

6.3. Future outlook

This study shows that the selected proxy for seasonal productivity anomaly (zcNDVI) could be accurately predicted with a simple OLR which had similar accuracies to a single DL model for all units that combined multiple predictors. Irrespective of the model used, the accuracy of prediction decreases with increasing lead time and latitude. The OLR could be expanded further in an attempt to boost its performance. One option for this could be to execute a principal component analysis (PCA) prior to regression. A PCA on all predictors per census unit could assist in better summarising the temporal variability within each unit; the first PCA component could then be used in the OLR at the cost of a more difficult interpretation of the resulting predictor variable. Other statistic methods to select predictors such as stepwise regression, or LASSO regression (Tibshirani, 1996) could be considered to improve OLR performances. Alternatively, we could cluster units with similar environmental characteristics (e.g. using the k-means applied in this study) and run OLR or the alternative regression approaches per cluster with increased sample size.

Additional spatio-temporal predictors can be incorporated into future implementation of both OLR and DL approaches. Examples include estimates of soil moisture, evapotranspiration, and existing multi-scalar drought indices. For example, satellite-derived soil moisture estimates have been used to predict NDVI anomalies (Asoka and Mishra, 2015; Tadesse et al., 2014). Another key variable relating to crop development is actual evapotranspiration. Currently operational satellite-derived evapotranspiration products exist at 1 km spatial resolution (Mu et al., 2007) with a reported relatively good accuracy ($R^2 = 0.70$) over cropland, when compared to eddy covariance data over the United States (Velpuri et al., 2013). Another index that combines the effect of temperature and precipitation is the SPEI (Vicente-Serrano et al., 2010), which is currently offered online as a gridded dataset at 0.5° resolution (http://spei.csic.es/database.html), but has the potential for calculation at finer spatial resolution using satellite-derived rainfall and evapotranspiration estimates. Another option to improve both methods may be using a larger sample size, for example by utilizing a longer NDVI time series (since 1981) derived from the Advanced Very High Resolution Radiometer (AVHRR) as incorporated in the GIMMS (Pinzón and Tucker, 2014) or the Long Term Data Record (LTDR; Sobrino and Julien, 2016) datasets. However, the balance between the pros of a longer time series against the cons of a reduced spatial resolution (i.e. 8 km) should be empirically tested. The prediction models used in this study can help in establishing an operational early warning system to achieve better preparedness for upcoming drought events. An operational system requires all input data to be available in near-real time. This is already the case for NDVI and rainfall, because NDVI data has only a four-day delay after the last date of the compositing period, and CHIRPS has a global rapid response product that is distributed two days after the end of each five-day period. The climatic indices PDO and MEI are updated once a month, resulting in a small delay when performing a prediction later in the month. In this study (Section 5.2.2) we showed that climatic indices without a lag and lagged at three and six months are most relevant for our predictions. Thus, climatic indices used without lag for the DL model is an issue that needs attention for operational implementation.

The proposed models could be easily implemented in other regions of the globe because the input satellite data for both vegetation (MOD13) and precipitation (CHIRPS v2) are available globally and in near real-time. For other regions, it is possible that different climatic oscillation indices can better explain the variation in vegetation productivity (e.g., Brown et al., 2010; Van Leeuwen et al., 2013) and should be selected accordingly. Similarly, the incorporation of other predictors, such as temperature, should be considered in areas of the globe where other climatic constraints to plant growth (Nemani et al., 2003) are more important. While a few challenges remain, we believe that the models presented in this study can constitute a solid basis for improved operational drought warnings.

7. Conclusion

Anticipating agricultural drought is a major research challenge. In this study, we showed that a combination of publicly-available satellite data with OLR and DL models has high skill in the prediction of vegetation productivity anomalies in a country that does not have a system in place for early prediction of agricultural drought. The global coverage of the data used in this study supports the testing of our approach in other drought prone regions.

We demonstrated that cumulative NDVI during the growing season, as a proxy for crop productivity, could be accurately predicted by DL and OLR models. This accuracy decreased for both approaches from north to south, particularly during predictions made earlier in the season. This gradient matches the gradient in season length, which partially reflects the fact that more information on the season performance was available for units with a longer LOS at the prediction lead time. Although scope exists to further improve the prediction models, the drought prediction tool developed in this study constitutes an important step for increased drought preparedness.

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